Inclass - Lab
(Week 3)

About the data set (Life Expectancy data)

The dataset contains information about several health and economic factors that contribute to average life expectancy for different countries.
Attribute information:

Country: Name of the country

Year: Year the observations were recorded

Status: Whether the country is Developed or Developing

Adult_Mortality: Mortality rate for age group 15-60 out of every 1000 individuals of the population

Infant_Deaths: Number of infant deaths per 1000 population

Alcohol: Alcohol, recorded per capita (15+) consumption (in litres of pure alcohol)

Hepatitis B: Hepatitis B (HepB) immunization coverage for 1 year olds (Percentage)

Measles: Number of reported cases for measles per 1000 from population

BMI: Average Body Mass Index for entire population

Underfive_Deaths: Number of deaths under 5 years of age per 1000 population

Polio: Polio (Pol3) immunization coverage for 1 year olds (Percentage)

Diphtheria: Diphtheria tetanus toxoid and pertussis (DTP3) immunization coverage for 1 year olds (Percentage)

HIV: Deaths per 1000 live births due to HIV/AIDS (0-4 years)

GDP: Gross Domestic Product per capita (in USD)

Population: Population of the country

Malnourished10_19: Prevalence of malnutrition among children and adolescents for Age 10 to 19 (Percentage)

Malnourished5_9: Prevalence of malnutrition among children for Age 5 to 9 (Percentage)

Income_Index: Human Development Index (HDI) in terms of national income per capita (index ranging from 0 to 1)

Schooling: Number of years of Schooling

Life_Expectancy: Life Expectancy in age for the country

Table of Content

Import the required libraries

In [ ]:
```
# type your code here
```

In [1]:
```
# import 'Pandas'
import pandas as pd

# import 'Numpy'
import numpy as np

# import subpackage of Matplotlib
import matplotlib.pyplot as plt

# import 'Seaborn'
import seaborn as sns

# to suppress warnings
from warnings import filterwarnings
filterwarnings('ignore')

# display all columns of the dataframe
pd.options.display.max_columns = None

# display all rows of the dataframe
pd.options.display.max_rows = None

# to display the float values upto 6 decimal places
pd.options.display.float_format = '{:.6f}'.format

# import train-test split
from sklearn.model_selection import train_test_split

# import various functions from statsmodels
import statsmodels
import statsmodels.api as sm

# import 'stats'
from scipy import stats

# 'metrics' from sklearn is used for evaluating the model performance
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error


# import function to perform linear regression
from sklearn.linear_model import LinearRegression

# import StandardScaler to perform scaling
from sklearn.preprocessing import StandardScaler

# import SGDRegressor from sklearn to perform linear regression with stochastic gradient descent
from sklearn.linear_model import SGDRegressor

# import function for ridge regression
from sklearn.linear_model import Ridge

# import function for lasso regression
from sklearn.linear_model import Lasso

# import function for elastic net regression
from sklearn.linear_model import ElasticNet

# import function to perform GridSearchCV
from sklearn.model_selection import GridSearchCV
```

In [2]:
```
# set the plot size using 'rcParams'
# once the plot size is set using 'rcParams', it sets the size of all the forthcoming plots in the file
# pass width and height in inches to 'figure.figsize'
plt.rcParams['figure.figsize'] = [15,8]
```

Load the Life expectancy dataset and display the first five records

```
In [16]: # load the csv file

         # type your code here
         df = pd.read_csv('Life_Expectancy.csv')
         # display the first five observations

         # type your code here
         df.head()
```

Out[16]:

	Country	Year	Status	Adult_Mortality	Infant_Deaths	Alcohol	Hepatitis B	Measles	BMI	Underfive_Deaths	Polio	Diphtheria	
0	Afghanistan	2015	Developing	263.000000	62	0.010000	65.000000	1154	19.100000	83	6	65	0.1
1	Albania	2015	Developing	74.000000	0	4.600000	99.000000	0	58.000000	0	99	99	0.1
2	Algeria	2015	Developing	19.000000	21	NaN	95.000000	63	59.500000	24	95	95	0.1
3	Angola	2015	Developing	335.000000	66	NaN	64.000000	118	23.300000	98	7	64	1.9
4	Antigua	2015	Developing	13.000000	0	NaN	99.000000	0	47.700000	0	86	99	0.2

Check the shape of the data and display its information

```
In [4]: # check the size of the dataframe
        df.shape
```

```
Out[4]: (182, 20)
```

```
In [5]: # display dataset information understand the dataset

        # type your code here
        df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 182 entries, 0 to 181
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Country           182 non-null    object 
 1   Year              182 non-null    int64  
 2   Status            182 non-null    object 
 3   Adult_Mortality   173 non-null    float64
 4   Infant_Deaths     182 non-null    int64  
 5   Alcohol           15 non-null     float64
 6   Hepatitis B       173 non-null    float64
 7   Measles           182 non-null    int64  
 8   BMI               178 non-null    float64
 9   Underfive_Deaths  182 non-null    int64  
 10  Polio             182 non-null    int64  
 11  Diphtheria        182 non-null    int64  
 12  HIV               182 non-null    float64
 13  GDP               157 non-null    float64
 14  Population        141 non-null    float64
 15  Malnourished10_19 178 non-null    float64
 16  Malnourished5_9   178 non-null    float64
 17  Income_Index      169 non-null    float64
 18  Schooling         173 non-null    float64
 19  Life_Expectancy   173 non-null    float64
dtypes: float64(12), int64(6), object(2)
memory usage: 28.6+ KB
```

Let's begin with some hands-on practice exercises

1. Data Preparation

1. The dataset gives the life expectancy for different countries. Check if any information about life expectancy is missing from the given records. How do we fix the problem if present?

```
In [27]: # type your code here
         df['Life_Expectancy'].isnull().sum()
```

```
Out[27]: 0
```

```
In [18]: na_data = df['Life_Expectancy'].isnull()
```

In [20]:
```
na_data.index[na_data == True].tolist()
```
Out[20]:
```
[46, 100, 104, 111, 118, 122, 135, 138, 168]
```

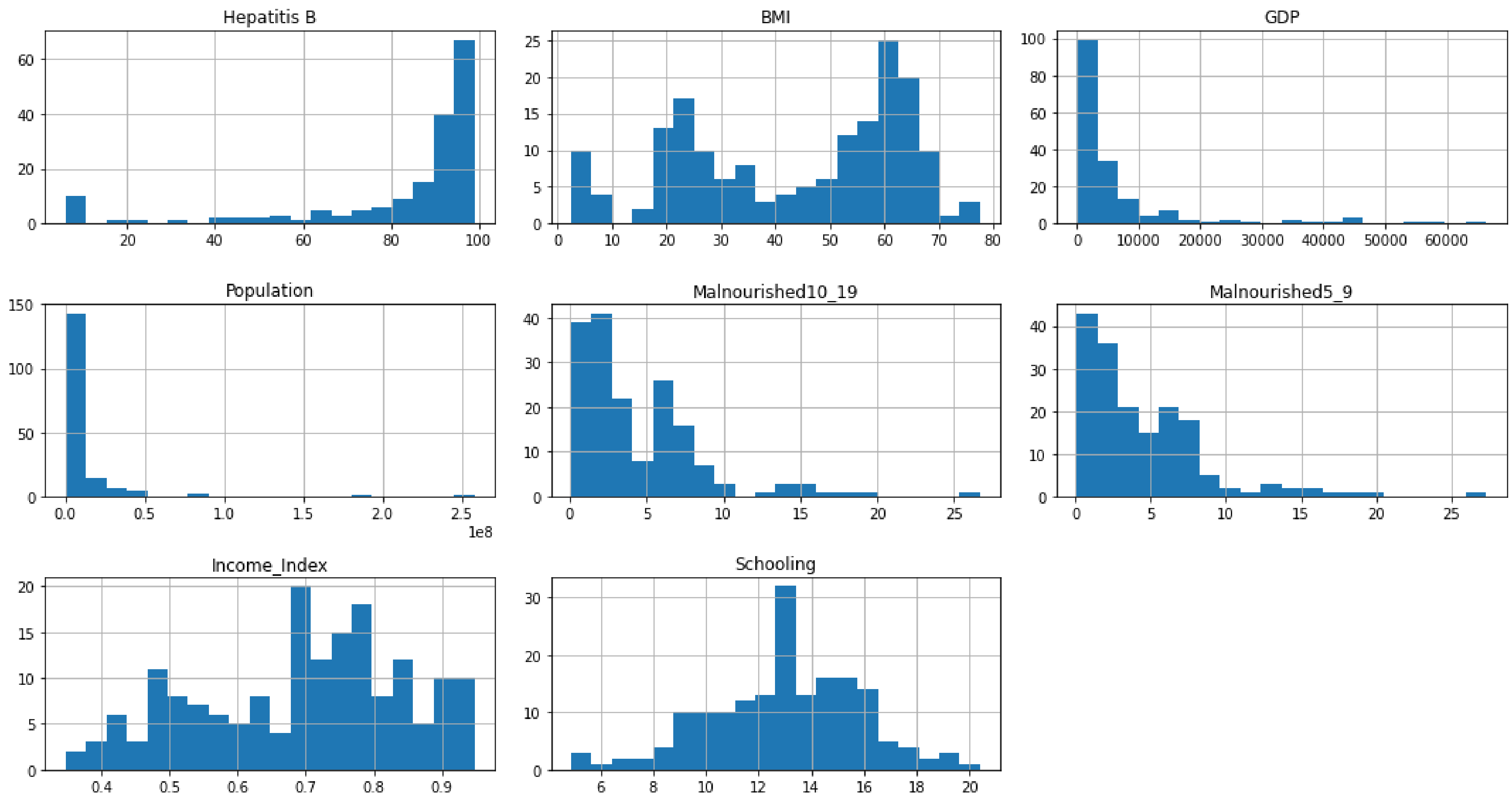
In [25]:
```
df = df.drop(df.index[[46, 100, 104, 111, 118, 122, 135, 138, 168]])
```

In [28]:
```
df.shape
```
Out[28]:
```
(173, 20)
```

2. How do we handle the missing values from the entire dataset?

In [30]:
```
# type your code here
df.isnull().sum()
```
Out[30]:
```
Country                  0
Year                     0
Status                   0
Adult_Mortality          0
Infant_Deaths            0
Alcohol                166
Hepatitis B              9
Measles                  0
BMI                      2
Underfive_Deaths         0
Polio                    0
Diphtheria               0
HIV                      0
GDP                     21
Population              34
Malnourished10_19        2
Malnourished5_9          2
Income_Index             7
Schooling                7
Life_Expectancy          0
dtype: int64
```

In [46]:
```
df_missing_values = df[['Hepatitis B','BMI','GDP','Population','Malnourished10_19',
                                 'Malnourished5_9','Income_Index','Schooling']]

# plot histogram of all variables which have missing values
# set the number of bins to 20
# set the figure size using 'figsize'
df_missing_values.hist(bins = 20, figsize = (15,8))

# adjust the subplots
plt.tight_layout()

# display the plot
plt.show()
```



In [34]:
```
df['Hepatitis B'] = df['Hepatitis B'].fillna(df['Hepatitis B'].median())
```

In [35]:
```
df['BMI'] = df['BMI'].fillna(df['BMI'].mean())
```

In [36]:
```
df['GDP'] = df['GDP'].fillna(df['GDP'].median())
```

In [37]:
```
df['Population'] = df['Population'].fillna(df['Population'].median())
```

In [38]:
```
df['Malnourished10_19'] = df['Malnourished10_19'].fillna(df['Malnourished10_19'].median())
```

In [39]:
```
df['Malnourished5_9'] = df['Malnourished5_9'].fillna(df['Malnourished5_9'].median())
```

In [40]:
```
df['Income_Index'] = df['Income_Index'].fillna(df['Income_Index'].mean())
```

In [41]:
```
df['Schooling'] = df['Schooling'].fillna(df['Schooling'].mean())
```

In [42]:
```
df.isnull().sum()
```

Out[42]:
```
Country                0
Year                   0
Status                 0
Adult_Mortality        0
Infant_Deaths          0
Alcohol              166
Hepatitis B            0
Measles                0
BMI                    0
Underfive_Deaths       0
Polio                  0
Diphtheria             0
HIV                    0
GDP                    0
Population             0
Malnourished10_19      0
Malnourished5_9        0
Income_Index           0
Schooling              0
Life_Expectancy        0
dtype: int64
```

In [44]:
```
df.drop('Alcohol', axis=1, inplace=True)
```

In [45]:
```
df.isnull().sum()
```

Out[45]:
```
Country              0
Year                 0
Status               0
Adult_Mortality      0
Infant_Deaths        0
Hepatitis B          0
Measles              0
BMI                  0
Underfive_Deaths     0
Polio                0
Diphtheria           0
HIV                  0
GDP                  0
Population           0
Malnourished10_19    0
Malnourished5_9      0
Income_Index         0
Schooling            0
Life_Expectancy      0
dtype: int64
```

3. Are there any redundant features in the data?

In [47]:
```
# type your code here
df.describe(include='object')
```

Out[47]:

	Country	Status
count	173	173
unique	173	2
top	Afghanistan	Developing
freq	1	141

In [48]:
```python
df.drop('Country', axis=1, inplace=True)
```

In [49]:
```python
df.describe()
```

Out[49]:

	Year	Adult_Mortality	Infant_Deaths	Hepatitis B	Measles	BMI	Underfive_Deaths	Polio	Diphtheria	HIV
count	173.000000	173.000000	173.000000	173.000000	173.000000	173.000000	173.000000	173.000000	173.000000	173.000000
mean	2014.988439	149.971098	22.872832	82.716763	1559.208092	43.466667	30.352601	83.040462	84.508671	0.647399
std	0.152057	95.679846	84.268577	24.066903	8055.443243	20.378109	108.428722	24.833951	22.687364	1.361795
min	2013.000000	1.000000	0.000000	6.000000	0.000000	2.500000	0.000000	5.000000	6.000000	0.100000
25%	2015.000000	74.000000	0.000000	81.000000	0.000000	24.400000	0.000000	84.000000	84.000000	0.100000
50%	2015.000000	137.000000	2.000000	93.000000	16.000000	51.000000	3.000000	93.000000	94.000000	0.100000
75%	2015.000000	199.000000	17.000000	97.000000	212.000000	61.600000	21.000000	97.000000	97.000000	0.300000
max	2015.000000	484.000000	910.000000	99.000000	90387.000000	77.600000	1100.000000	99.000000	99.000000	9.300000

In [50]:
```python
df['Year'].value_counts()
```

Out[50]:
```
2015    172
2013      1
Name: Year, dtype: int64
```

In [51]:
```python
df.drop('Year', axis=1, inplace=True)
```

In [52]:
```python
df.drop('Infant_Deaths', axis=1, inplace=True)
```

In [53]:
```python
df.shape
```

Out[53]:
```
(173, 16)
```

4. Perform dummy encoding for appropriate variables of the dataset if required

In [54]:
```python
# type your code here
df['Status'] = pd.get_dummies(data=df['Status'],drop_first=True)
```

In [55]:
```python
df.head()
```

Out[55]:

	Status	Adult_Mortality	Hepatitis B	Measles	BMI	Underfive_Deaths	Polio	Diphtheria	HIV	GDP	Population	Malnouri
0	1	263.000000	65.000000	1154	19.100000	83	6	65	0.100000	584.259210	33736494.000000	
1	1	74.000000	99.000000	0	58.000000	0	99	99	0.100000	3954.227830	28873.000000	
2	1	19.000000	95.000000	63	59.500000	24	95	95	0.100000	4132.762920	39871528.000000	
3	1	335.000000	64.000000	118	23.300000	98	7	64	1.900000	3695.793748	2785935.000000	
4	1	13.000000	99.000000	0	47.700000	0	86	99	0.200000	13566.954100	2174645.000000	

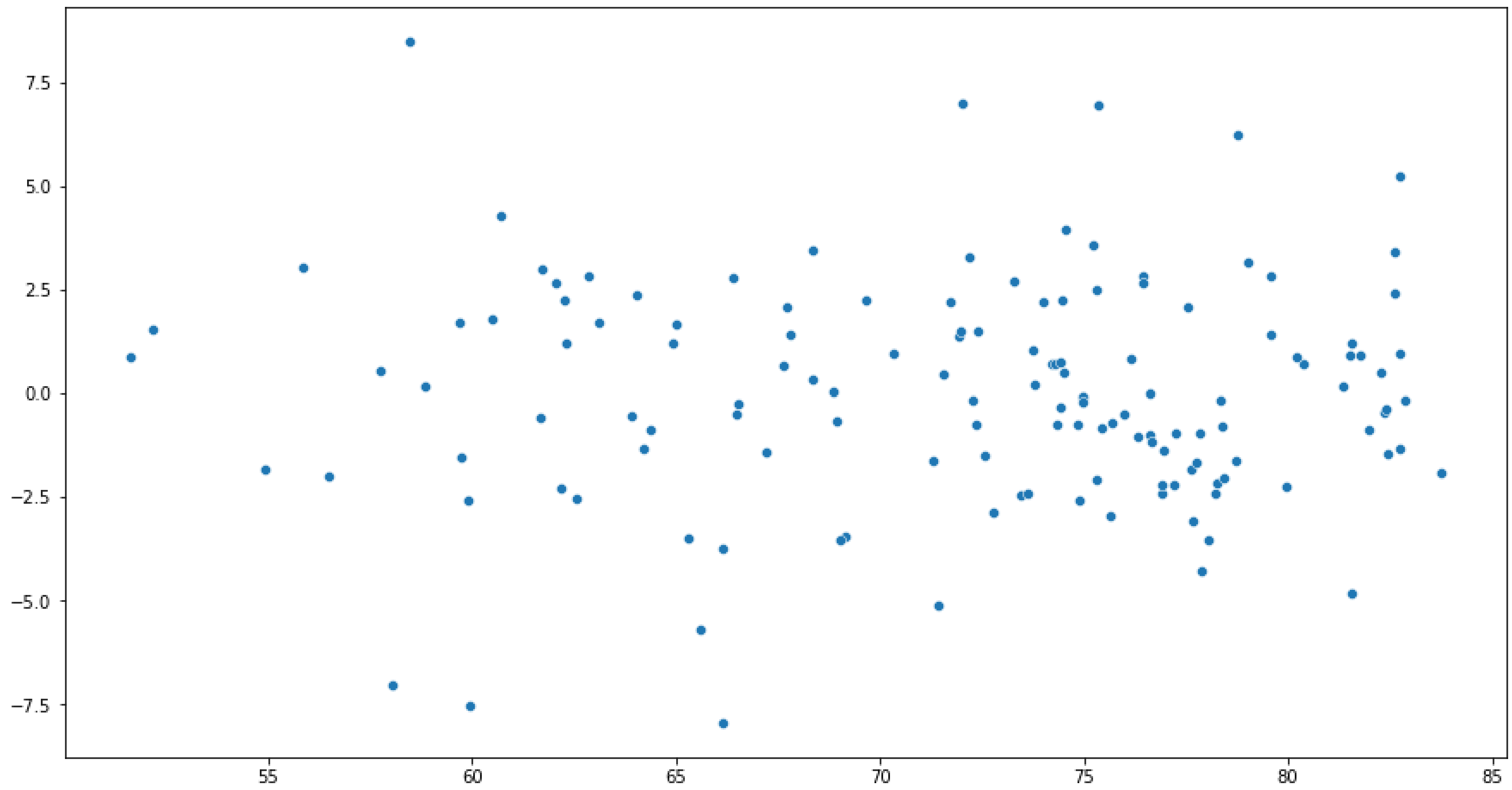
2. Linear Regression

5. Build a full model on the given data. Check whether the obtained residuals have constant variance

In [56]:
```python
# type your code here
X = df.iloc[:,:15]
X = sm.add_constant(X)
y = df['Life_Expectancy']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=10, test_size=0.2)
MLR_model = sm.OLS(y_train, X_train).fit()
```

In [58]:
```
y_pred = MLR_model.fittedvalues
residuals = MLR_model.resid
sns.scatterplot(x=y_pred,y= residuals)
```

Out[58]: <AxesSubplot:>



In [ ]:
```
# There is no pattern seen in the scatterplot hence the data contains constant variance.
```

6. Build a model to study the impact of immunization on life expectancy, using least squares regression. Find the unexplained variation for the model

In [59]:
```
# type your code here
X = df.iloc[:,[2,6,7]]
y = df['Life_Expectancy']

linreg = LinearRegression()
MLR_model = linreg.fit(X,y)
y_pred = MLR_model.predict(X)
residual = np.array(y - y_pred)

unexplained_var = np.sum(residual**2)
print(unexplained_var)
```

```
7272.4649163342965
```

7. Build a model to study the impact of malnutrition on life expectancy, using least squares regression. Interpret the coeffients

In [60]:
```
# type your code here
X = df.iloc[:,[11,12]]
X = sm.add_constant(X)
y = df['Life_Expectancy']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=10, test_size=0.2)
MLR_model = sm.OLS(y_train, X_train).fit()
MLR_model.summary()
```

Out[60]:

OLS Regression Results

Dep. Variable:	Life_Expectancy	**R-squared:**	0.226
Model:	OLS	**Adj. R-squared:**	0.214
Method:	Least Squares	**F-statistic:**	19.66
Date:	Sun, 19 Mar 2023	**Prob (F-statistic):**	3.20e-08
Time:	11:15:31	**Log-Likelihood:**	-466.03
No. Observations:	138	**AIC:**	938.1
Df Residuals:	135	**BIC:**	946.8
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	76.3070	0.916	83.320	0.000	74.496	78.118
Malnourished10_19	-0.5024	0.769	-0.654	0.514	-2.023	1.018
Malnourished5_9	-0.3930	0.754	-0.521	0.603	-1.884	1.098

Omnibus:	6.049	**Durbin-Watson:**	1.840
Prob(Omnibus):	0.049	**Jarque-Bera (JB):**	6.225
Skew:	-0.512	**Prob(JB):**	0.0445
Kurtosis:	2.820	**Cond. No.**	16.1

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

3. Gradient Descent

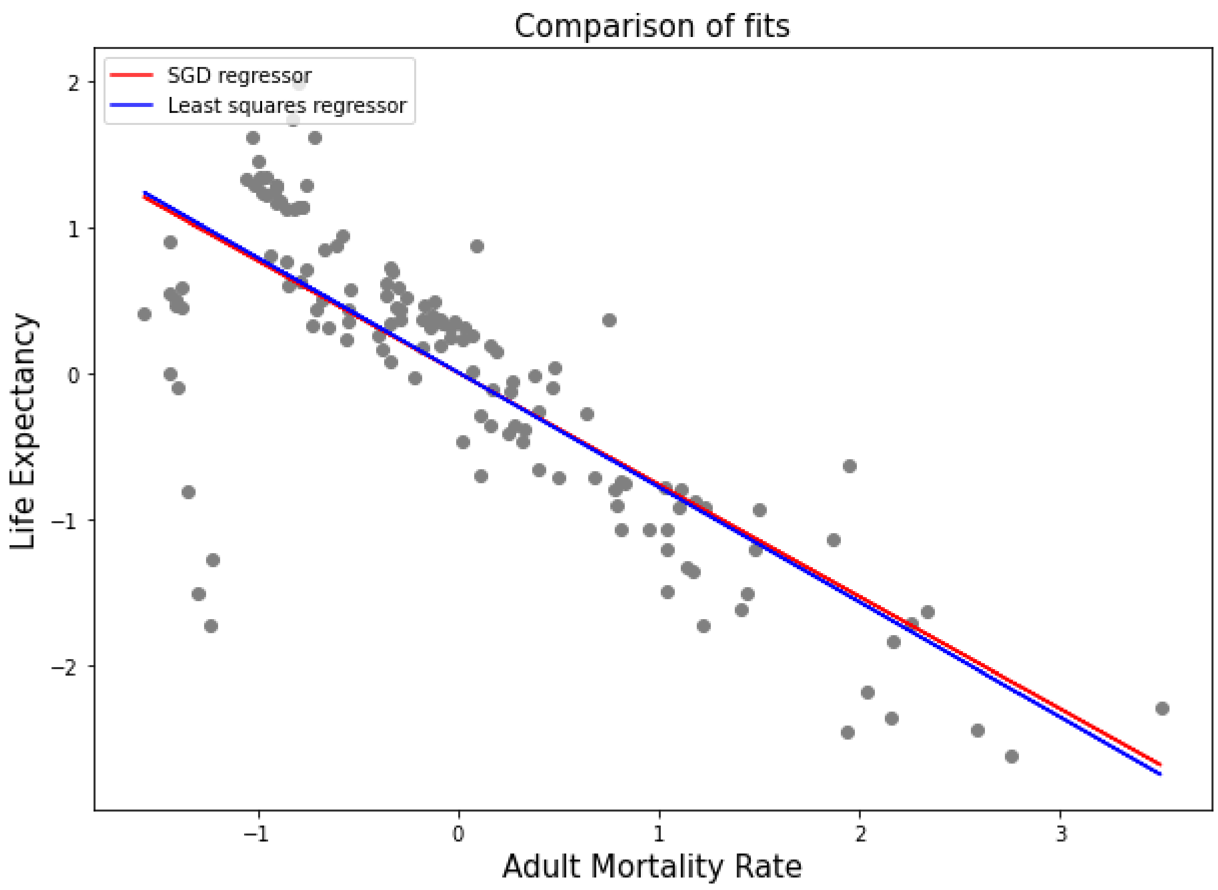
8. Build a model to study the influence of adult mortality rate on life expectancy using both the least squares regression and gradient descent approach. Are the fits for both the models different?

In [61]:
```
# type your code here
X = df.iloc[:,1].values
X = X.reshape(-1,1)

# set the dependent variable
y = df['Life_Expectancy']

# initialize the standard scalar
X_scaler = StandardScaler()

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.2)
```

In [62]:
```
linreg = LinearRegression()
MLR_model = linreg.fit(X_train,y_train)
linpred = MLR_model.predict(X_train)
```

In [63]:
```
sgd = SGDRegressor()
MLR_model_sgd = sgd.fit(X_train,y_train)
sgdpred = MLR_model_sgd.predict(X_train)
```

```
In [64]: # set the figure size
plt.figure(figsize=(10,7))

# plot the scatter plot
# colors: set the color of the points in the scatter plot
plt.scatter(X_train, y_train,color='grey')

# set xlabel for the plot
plt.xlabel("Adult Mortality Rate",fontsize = 15)

# set ylabel for the plot
plt.ylabel("Life Expectancy",fontsize = 15)

# set title for the plot
plt.title("Comparison of fits",fontsize = 15)

# plot the regression line for the two models
# color: set the color of the line
# label: set the label of the line for the legend
plt.plot(X_train,sgdpred,color='red',label='SGD regressor')
plt.plot(X_train,linpred,color='blue',label='Least squares regressor')

# set the position of legend
plt.legend(loc='upper left')

# disply the plot
plt.show()
```



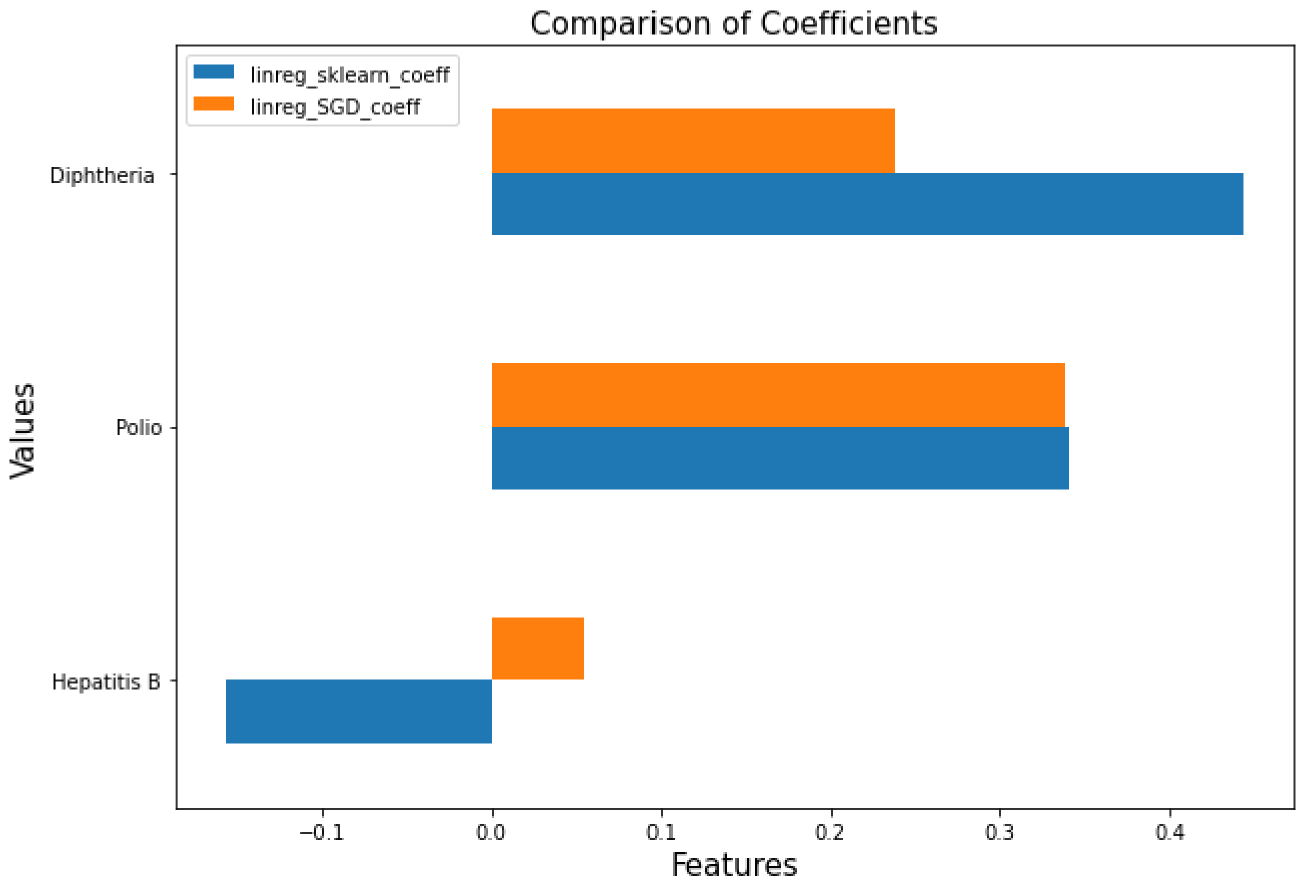
9. Build a model to analyze the influence of immunization on life expectancy. Use SGD and plot a horizontal multiple barchart to compare the values of beta coefficients with values obtained by the full model build least squares regression.

```
In [68]: # type your code here
X = df.iloc[:,[2,6,7]]


# set the dependent variable
y = df['Life_Expectancy']

# initialize the standard scalar
X_scaler = StandardScaler()

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.2)
```

```
In [69]: sgd1 = SGDRegressor()
MLR_model_sgd1 = sgd1.fit(X_train,y_train)
```

In [70]:
```python
linreg = LinearRegression()
MLR_model1 = linreg.fit(X_train,y_train)
```

In [71]:
```python
df_immunization=df.iloc[:,[2,6,7]]

df_coeff = pd.DataFrame([MLR_model1.coef_, MLR_model_sgd1.coef_], columns = df_immunization.columns,
                 index = ['linreg_sklearn_coeff', 'linreg_SGD_coeff'])

fig = df_coeff.T.plot.barh( figsize=(10,7))

# set axes and plot labels
# set the text size using 'fontsize'
plt.title('Comparison of Coefficients', fontsize = 15)
fig.set_xlabel('Features', fontsize = 15)
fig.set_ylabel('Values', fontsize = 15)

# set the x-axis labels horizontally
plt.xticks(rotation = 'horizontal')

# set the position of legend
fig.legend(loc='upper left')

# display the plot
plt.show()
```



In [ ]:
```python
# For polio both the model interpretations are nearly similar
# For diptheria the linreg coeff are higher than SGD.
# For hepatitis B the SGD coeff are higher and the lin reg coeff have gone towards negative.
```

10. Build a full model using least squares regression. Check whether the model overfits the training data or not.

In [78]:
```python
# type your code here
X = df.iloc[:,:15]
y = df['Life_Expectancy']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.2)

linreg = LinearRegression()
MLR_model2 = linreg.fit(X_train,y_train)
```

In [79]:
```python
# Train
train_pred = MLR_model2.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
```

In [80]:
```python
# Test
test_pred = MLR_model2.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
```

In [81]:
```python
print(mse_train,rmse_train)
print(mse_test,rmse_test)
```

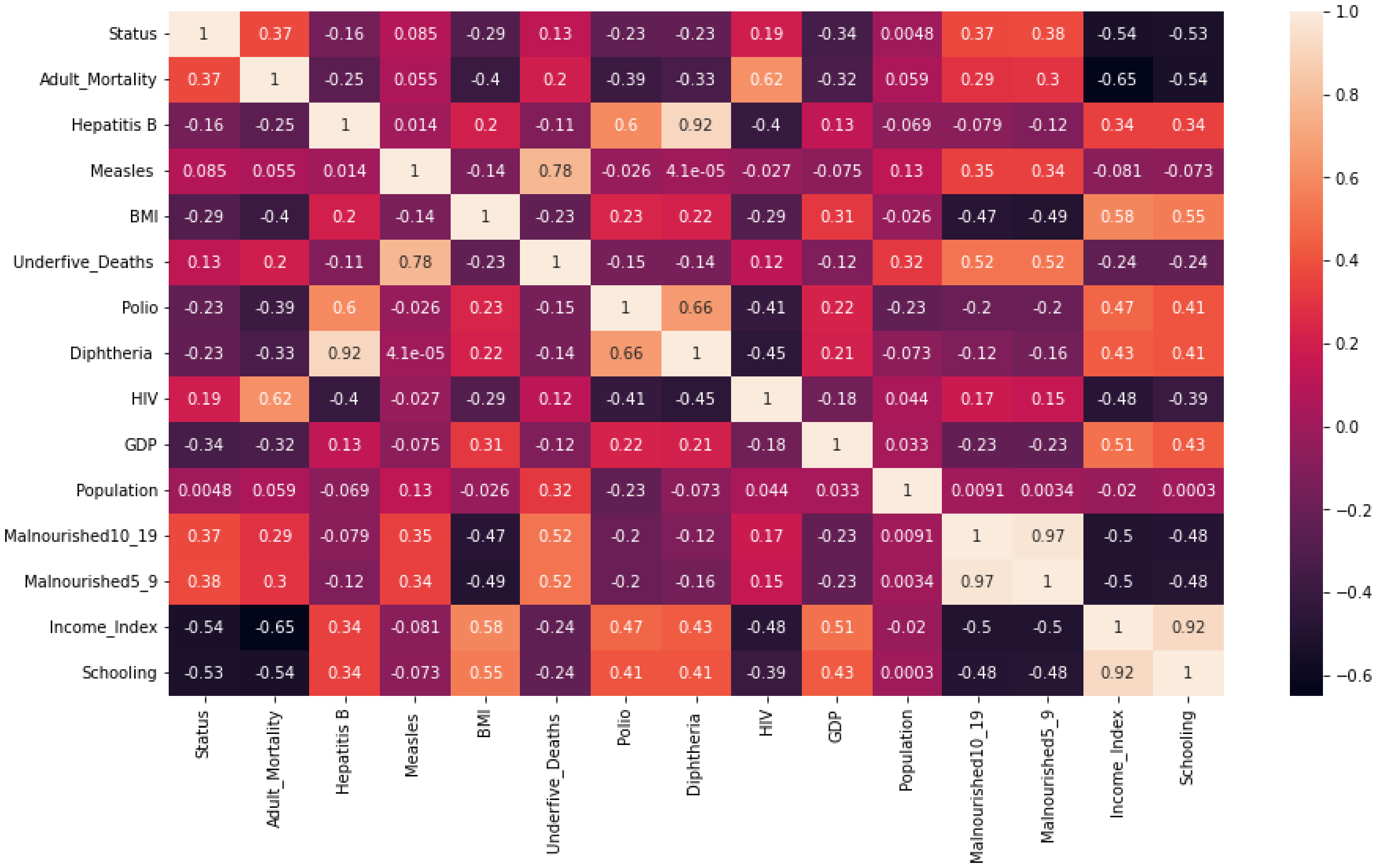
```
7.0590856828921575 2.6569
11.72600488499266 3.4243
```

11. Can we use a linear regression model to analyze how all features from the dataset impact life expectancy?

In [ ]:
```python
# type your code here
# Yes we can use linear regression because the target variable is numerical and is dependent on independent variables
```

In [85]:
```python
df_features = df.iloc[:,:15]
sns.heatmap(df_features.corr(),annot=True)
```

Out[85]: <AxesSubplot:>



4. Regularization

12. Can we perform regression analysis without eliminating features involved in multicollinearity detected in question 11?

In [90]:
```python
# type your code here
X = df.iloc[:,:15]


# set the dependent variable
y = df['Life_Expectancy']

# initialize the standard scalar
X_scaler = StandardScaler()

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 110, test_size = 0.2)
```

In [91]:
```
ridge = Ridge(alpha=5.5)
ridge_model = ridge.fit(X_train, y_train)
```

In [92]:
```
# Train
train_pred = ridge_model.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
```

```
0.3528
```

In [93]:
```
# Test
test_pred = ridge_model.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
0.3533
```

In [ ]:
```
# Ridge
```

13. Build a model to study the impact of diseases and immunization on life expectancy. Identify the significant variables from the model. Use 'alpha = 1.5' if required.

In [94]:
```
# type your code here
# type your code here
X = df.iloc[:,[2,3,6,7,8]]


# set the dependent variable
y = df['Life_Expectancy']

# initialize the standard scalar
X_scaler = StandardScaler()

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.2)
```

In [95]:
```
ridge = Ridge(alpha=1.5)
ridge_model = ridge.fit(X_train, y_train)
```

In [96]:
```
# Train
train_pred = ridge_model.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
```

```
0.7101
```

In [97]:
```
# Test
test_pred = ridge_model.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
0.7136
```

In [98]:
```
X = df.iloc[:,[2,3,6,7,8]]
X = sm.add_constant(X)
y = df['Life_Expectancy']

MLR_model3 = sm.OLS(y_train,X_train).fit()
```

In [100]:
```
# Train
train_pred = MLR_model3.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
```

```
0.7102
```

In [101]:
```
# Test
test_pred = MLR_model3.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
0.7117
```

In [102]:
```
MLR_model3.summary()
```

Out[102]:

OLS Regression Results

Dep. Variable:	Life_Expectancy	**R-squared (uncentered):**	0.498
Model:	OLS	**Adj. R-squared (uncentered):**	0.479
Method:	Least Squares	**F-statistic:**	26.39
Date:	Sun, 19 Mar 2023	**Prob (F-statistic):**	1.87e-18
Time:	12:18:25	**Log-Likelihood:**	-148.59
No. Observations:	138	**AIC:**	307.2
Df Residuals:	133	**BIC:**	321.8
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	-0.1130	0.138	-0.821	0.413	-0.385	0.159
x2	-0.0663	0.057	-1.168	0.245	-0.179	0.046
x3	0.2707	0.081	3.355	0.001	0.111	0.430
x4	0.2251	0.156	1.441	0.152	-0.084	0.534
x5	-0.4345	0.065	-6.673	0.000	-0.563	-0.306

Omnibus:	7.053	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.029	**Jarque-Bera (JB):**	6.767
Skew:	-0.457	**Prob(JB):**	0.0339
Kurtosis:	3.584	**Cond. No.**	5.23

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

14. Build a model to study the impact of malnutrition and diseases on life expectancy. Identify the insignificant variables from the model. Use 'alpha = 1' if required.

In [ ]:
```
# type your code here
X = df.iloc[:,[3,8,12,11]]
X = sm.add_constant(X)
y = df['Life_Expectancy']

MLR_model4 = sm.OLS(y_train,X_train).fit()
```

In [117]:

```
# type your code here
# type your code here
X = df.iloc[:,[3,8,12,11]]


# set the dependent variable
y = df['Life_Expectancy']

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 30, test_size = 0.2)
```

In [118]:

```
lasso = Lasso(alpha = 1)
lasso_model = lasso.fit(X_train, y_train)
```

In [119]:

```
MLR = LinearRegression()
lin_model = MLR.fit(X_train, y_train)
```

In [120]:

```
# Train
train_pred = lin_model.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
# Test
test_pred = lin_model.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
0.6853
0.7967
```

In [121]:

```
# Train
train_pred = lasso_model.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
# Test
test_pred = lasso_model.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
1.0039
0.9813
```

15. Build a full model using the elastic net regression. Use 'alpha = 0.1' and 'l1_ratio=0.001'. Also, compute the RMSE for train and test sets.

In [123]:

```
# type your code here
# type your code here
# type your code here
X = df.iloc[:,:15]


# set the dependent variable
y = df['Life_Expectancy']

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 110, test_size = 0.2)
```

In [124]:
```
e_net = ElasticNet(alpha=0.1,l1_ratio=0.001)
e_net_model = e_net.fit(X_train, y_train)
```

In [125]:
```
# Train
train_pred = e_net_model.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
# Test
test_pred = e_net_model.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
0.3581
0.3544
```

16. Build a full model. Identify the features that are significantly influencing the life expectancy. Use 'alpha = 0.5' if required.

In [126]:
```
# type your code here
# type your code here
# type your code here
X = df.iloc[:,:15]


# set the dependent variable
y = df['Life_Expectancy']

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 110, test_size = 0.2)
```

In [127]:
```
MLR1 = LinearRegression()
lin_model1 = MLR1.fit(X_train, y_train)
```

In [128]:
```
# Train
train_pred = lin_model1.predict(X_train)

mse_train = mean_squared_error(y_train,train_pred)
rmse_train = round(np.sqrt(mse_train),4)
print(rmse_train)
# Test
test_pred = lin_model1.predict(X_test)

mse_test = mean_squared_error(y_test,test_pred)
rmse_test = round(np.sqrt(mse_test),4)
print(rmse_test)
```

```
0.35
0.3606
```

5. Grid Search

17. If ridge regression is used to build a full model. Which value is the best alpha from the list of values?

Consider the alpha values: [7,8,9,10,11]

In [130]:
```
# type your code here
X = df.iloc[:,:15]


# set the dependent variable
y = df['Life_Expectancy']

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 110, test_size = 0.2)
```

In [132]:
```
tuned_param = [{'alpha':[7,8,9,10,11]}]
ridge = Ridge()
ridge_grid = GridSearchCV(estimator=ridge,param_grid=tuned_param,cv=5)
ridge_grid.fit(X_train,y_train)

print(ridge_grid.best_params_)
```

```
{'alpha': 11}
```

In [ ]:
```

```

18. If lasso regression is used to build a full model. Which value is the best alpha from the list of values?

Consider the alpha values: [7,8,9,10,11]

In [133]:
```
# type your code here
X = df.iloc[:,:15]


# set the dependent variable
y = df['Life_Expectancy']

# standardize all the columns of df_lifeExp
X = X_scaler.fit_transform(X)

# standardize the target explicitly and storing it in a new variable 'y'
y = (y - y.mean()) / y.std()

# split data into train subset and test subset
# set 'random_state' to generate the same dataset each time you run the code
# 'test_size' returns the proportion of data to be included in the test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 110, test_size = 0.2)
```

In [134]:
```
tuned_param = [{'alpha':[7,8,9,10,11]}]
lasso = Lasso()
lasso_grid = GridSearchCV(estimator=lasso,param_grid=tuned_param,cv=5)
lasso_grid.fit(X_train,y_train)

print(lasso_grid.best_params_)
```

```
{'alpha': 7}
```

19. Perform regression analysis to study the impact of malnutrition and diseases on life expectancy. Determine the optimal value of alpha and mixing parameter if elastic net regression is used to build the model. Consider the following list of values:

alpha : [0.1,0.5,1,1.5,2,2.5,3,3.5,4]
l1_ratio : [0.5,0.55,0.6,0.65,0.7,0.75,0.8,0.85,0.9]

In [136]:
```
# type your code here
X = df.iloc[:,[3,8,11,12]]
y = df['Life_Expectancy']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.2)
```

```
In [137]: tuned_param = [{'alpha':[0.1,0.5,1,1.5,2,2.5,3,3.5,4],'l1_ratio':[0.5,0.55,0.6,0.65,0.7,0.75,0.8,0.85,0.9]}]
e_net1 = ElasticNet()
enet_grid = GridSearchCV(estimator=e_net1,param_grid=tuned_param,cv=5)
enet_grid.fit(X_train,y_train)

print(enet_grid.best_params_)
```

```
{'alpha': 0.1, 'l1_ratio': 0.9}
```

20. Build a full model. Select the optimal value for elastic net mixing parameter if the alpha value is 0.8

Consider the values: l1_ratio : [0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1]

```
In [142]: # type your code here
X = df.iloc[:,:15]
y = df['Life_Expectancy']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 110, test_size = 0.2)
```

```
In [143]: tuned_param = [{'l1_ratio':[0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1]}]
e_net2 = ElasticNet(alpha=0.8)
enet_grid2 = GridSearchCV(estimator=e_net2,param_grid=tuned_param,cv=5)
enet_grid2.fit(X_train,y_train)

print(enet_grid2.best_params_)
```

```
{'l1_ratio': 1}
```